DROUGHT PATTERN INVESTIGATION THROUGH PROCESSING NORMALIZED VEGETATION INDEX-BASED SATELLITE IMAGES

By

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ABSTRACT

The emergence of satellite remote sensing technology has provided people with various appropriate, more accurate and easy to use tools for monitoring environmental conditions like health of vegetation. Using the red and infrared band reflectances, for instance, enables the derivation of a vegetation index called Normalized Difference Vegetation Index (NDVI) in spatial and temporal domains. This index is vital to assess the evolution of drought as well as predict crop yield.

The aim of this study is to analyze the series of deviation of NDVI images, extract virtual drought objects from the series, and investigate for drought patterns from historical images for growing season after appropriate preprocessing and segmentation of the images.

In this study, the virtual drought objects extracted from images over the growing season (June -September) were found to exhibit a given (similar) pattern for the historical drought years, taken in Ethiopia. The graphical pattern exhibited by historical occurrences of drought for specific area on the ground demonstrated nearly a similar time series except the fact that the intensities vary. This variance is an indicative of the difference in the severity level of the droughts at each specific area. Hence, given the implementation of appropriate prediction tool, this similarity in the time series analysis of the historical data over a drought will give new views for ways in drought prediction for early warning and crop condition monitoring at near real-time.

Keywords: Drought Prediction, NDVI Images, Virtual Drought Object, Pattern.

INTRODUCTION

Drought, an unusual variation in climate condition, is an ecological incident which is manifested in the reduction of farming production (Huang & Jiang, 2001). It's a protracted period of deficient precipitation which causes extensive damage to crops, and results in loss of yield. To this end, various drought assessment and monitoring missions has been conducted to either minimize or avoid the damage inflicted on life as a result.

But the efforts so far have been based on conventional methods that rely on the availability of meteorological point data like amount of rainfall and the related indices. These methods require a tiresome data collection, and provide a scarce information as a given data represents a wide geographical region. This makes the approach an unreliable to take risk measures as precaution. Therefore, producing a more reliable and an all round information for concerned bodies is very important.

Since recently, the availability of data from remote sensing technology has been engrossing wider attention as it overcomes the limitations of the traditional drought indices. Remote sensing data or data from satellite sensors can provide continuous datasets that can be used to detect the onset of a drought, its duration and magnitude (Thiruvengadachari & Gopalkrishana, 1993). These sensors capture spectral bands reflected from the surface of earth and provide information for monitoring green vegetation conditions on the ground: dense, scarce, or depleted.

Through thorough scientific investigations, researchers have tried to derive information from satellite images to accompany with other ecosystem's data for better and more accurate prediction of drought (Sharma, 2007). The image-based analysis produces better results, especially, for areas where ground monitoring using other meteorological data is scarce. This approach requires a good knowledge of image processing for relevant feature extraction.

The remote sensing satellites provide continuous data at specific intervals (e.g., Meteosat Second Generation (MSG) data for every 15 minutes). Thus, the available information is bulky, and difficult for decision makers to analyze (FEWSNET, 2009). In addition, even though drought has its own state and behavior, there had been little efforts exerted so far to detect drought by its own properties as *spatial object* (Rulinda et al., 2009). These virtual objects are non-physical features on the ground, but the measurements having geographic information (Huang & Jiang, 2001). Pixels of similar spectral reflectance and closer spatial locations grouped to define object of interest.

Temporal and spatial patterns of drought vary from one time to another and an area to another (Wilhite, 2000; Michael, 1999). For a specific area, if relationships between drought object characteristics are identified with a certain time lag, taking appropriate action based on the associations may reduce the impacts of future droughts. To monitor drought and help in drought decision making, this study has attempted to identify relationships (patterns) between consecutive drought objects for a given spatial location using time series data-mining. This has the potential to assist in pro-active drought decision making including mitigation and drought risk management. For this purpose, a time series data analysis has been used to investigate the patterns that drought objects might exhibit over time for a given spatial location to help in drought monitoring.

1. Objectives

The main objective of this work is to analyze the drought patterns over time for historical drought areas from NDVI based satellite images. Thus, the specific objectives intended to be addressed are:

- To analyze NDVI based satellite images for determining how drought can be defined
- To select appropriate image processing technique for proper pre-processing and segmentation.
- Extract features of drought objects.
- Develop the graph showing the pattern of drought objects over time.

2. Preprocessing of Remote Sensing Data

2.1 Derivation of Drought Indices

The development of earth observation satellites from 1980 onwards equipped with sensors mainly in the optical domain opened a new road for drought monitoring and detection. This technology allowed for the derivation of truly spatial information at global or regional coverage at a consistent method and a high repetition rate. The commonly used remote sensing-based drought indices are the Normalized Vegetation Index (NDVI), first applied for drought monitoring by Tucker and Choudhary (1987) and the Standard Vegetation Index (SVI) by Peters, Walter Shea, Vina, Hayes, and Svoboda (2000).

A healthy green vegetation condition is characterized by a maximum absorption radiation in the red and large reflection in the neighboring near-infrared region (Sharma, 2007). In addition, for unhealthy vegetation condition, the reflectance in red region increases while in near infrared region decreases. Combining these properties, Tucker's vegetation index (NDVI) is produced as follows (Musaningabe, 2007):

$$\mathrm{NDVI} = (\lambda_{NIR} - \lambda_{RED}) / (\lambda_{NIR} + \lambda_{RED}) \tag{1}$$

Where λ_{NIR} and λ_{RED} are the reflectance in the NIR and RED band, the values vary in [-1, 1].

As NDVI is not sensitive to influences of soil background reflectance at low vegetation cover and lag vegetation response to precipitation deficiency. NDVI itself does not reflect drought or non-drought condition (Siqi, 2011). But the anomaly of NDVI from its long term mean can define drought. The deviation of NDVI is calculated as the difference between the NDVI at current time step, such as ten day period (dekadal), and a long-term mean of the same time step for each pixel. The formula is given as (Musaningabe, 2007):

$$NDVI_{dev} = NDVI_{i,dekad} - NDVI_{i,mean} \quad (2)$$

Where $NDVI_{i,dekad}$ is the value for the i^{th} dekad, and $NDVI_{i,mean}$ is the long term mean value of the historical $NDVI_i$ for same time dekad i which is given as

$$NDVI_{i,mean} = \frac{1}{N} \times \sum_{I=1}^{N} NDVI_i \quad (3)$$

Where N is the number of historical *NDVI* images considered for the mean computation and $NDVI_{dev}$ value range is between -1 and 1.

The severity level of crop unhealthy condition is measured in terms of $NDVI_{dev}$ value. More the deviation is closer to -1, worse the vegetation health (Getachew, Tsegaye, Solomon, & Shawndra, 2010).

2.2 Denoising

The presence of some insufficient registrations and noisy regions due to missing values like the white region (like water body) in the samples necessites the application of image noise minimization step. Therefore, the image smoothing approach using anisotropic diffusion was applied to each and every image in the series. The equation for anisotropic diffusion is (Weeratunga & Kamath, 2002):

$$\begin{cases} \dfrac{\partial I}{\partial t} = div(c(|\nabla I|).\nabla I) \\ I(t=0) = I_o \end{cases} \quad (4)$$

Here, I_o is the original image, *I* is the evolution result of the original image at different time t, *div* is the divergence operator, ∇ is a gradient operator and c is the diffusion coefficient given by either of the options according to Perona and Malik(1990) proposals:

$$c(x) = \frac{1}{1+(\nabla I/k)^2} \qquad OR \qquad c(x) = \exp(-(\nabla I/k)^2) \quad (5)$$

Where, k is the diffusion parameter.

2.3 Segmentation to Extract Virtual Drought Object

The purpose of the segmentation step is to partition an image into meaningful virtual drought objects of different classes (e.g. low, medium, severe drought objects, etc) and background region with normal vegetation condition. In this work the intention was to mark the boundaries of group of pixels that defines a given drought object. As the intensity values of pixels are of great importance, modification of these values affects the final information. Hence, the values were retained using the segmentation approach only for masking. For this purpose, the k-means clustering algorithm which was used to produce the different clusters of an image region. The points are clustered around centroids $\mu_i, \forall i = 1....K$ which are obtained by minimizing the objective (Tatiraju & Mehta, 2008)

$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2 \quad (6)$$

Where there are k clusters S_i, $i = 1, 2,..., k$ and μ_i is the centroid or mean point of all the points $X_j \in S_i$. In this work the iterative version of the algorithm is employed.

3. Results and Discussion

Historical occurrences of most prevalent drought incidence were found to be in the years 1984, 2002, and 2009 in Ethiopia. During those times, different regions were suffering from shortage of crop yield, and hence famine. For example, in 1984 drought occurred in North Eastern part of the country. Hence, these historical records were used in this research.

3.1 Noise Removal

The selection of area of interest is based on historical occurrence of drought is shown in Figure 1. This is the first step towards denoising. This process is repeated for every image in the whole growing season (June to September).

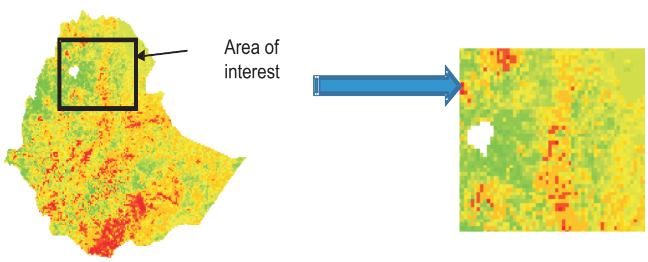

Figure 1. AOI to Show the Series of Dekadal

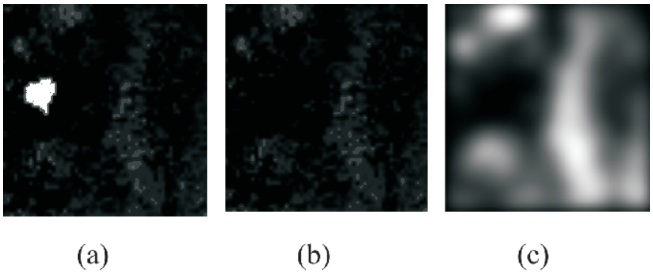

Figure 2. Noise Removal (a) Original Image (b) Image After Removing Sharp False Values (c) Denoised Image Using Anisotropic Diffusion

With the application of anisotropic diffusion to an image from the AOI selected in Figure 1, the images before and after denoising for an area selected from the North Eastern part of Ethiopia (shown in Figure 1) is shown in Figure 2.

The above procedure is repeated for every image in different dekadals of a given study region to accompany for the time series analysis. The series was the growing season of a given year which in this study includes the months of June to September.

3.2 Segmentation

After noise was removed/minimized, segmentation using the k-mean clustering approach was applied. This method requires the number of clusters k as an input. Therefore, the performance metric used was the one evaluated in terms of a simple validity measure based on the intra-class and inter-class distance measures. This evaluation was applied to different images in a given series and most of which yielded a value similar to that shown in Table 1.

According to the experimental output of Table 1, the optimum number of clusters that minimizes the intra-to-inter cluster ratio was found to be five (5). In general, this number of clusters (five) was used for segmentation of an image into different classes of drought objects and background.

To retain the pixel values unchanged, the segmented image was used just to overlay on the original image for locating the groups of pixels defining a drought object. Accordingly, the objects having similar intensities in the segmented (masking) image were extracted from the original (non-segmented) image.

The segmentation procedure in Figure 3 was applied to all the images in a series. Using those uniform regions in the segmentation results, the objects from the original images were extracted. For instance, a rectangular region in Figure 4 shows a very severe drought. Thus, this rectangular region was overlaid on the original image to extract the drought object belonging to very severe drought class. The extraction for all the twelve images in the series was performed and sample is shown in Figure 4.

This object extraction procedure was applied to all the

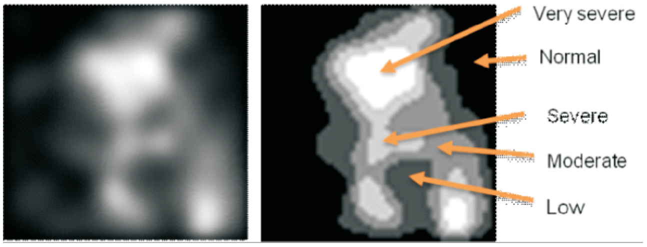

Figure 3. Segmentation Using K-Means Clustering: to the Left is the Image before Segmentation and to the Right is Segmented (Masking) Image

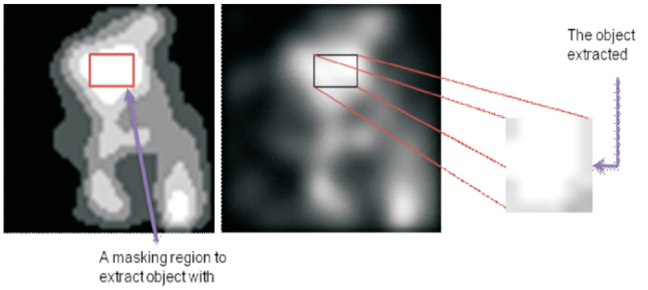

Figure 4. Sample Area Used as Mask (left) and Extracting Objects Using the Masks (right)

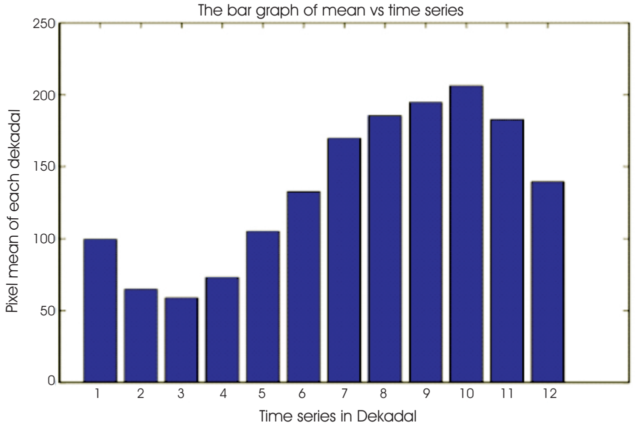

Figure 5. The Bar Graph of Intensity Means of Drought Objects Over Twelve Dekadals

No. clusters	2	3	4	5	6	7	8	9	10
intra/ inter	0.0867	0.0594	0.0416	0.0356	0.0488	0.0382	0.0398	0.0454	0.0461

Table 1. Intra-to-Inter Cluster Ratios for Clusters

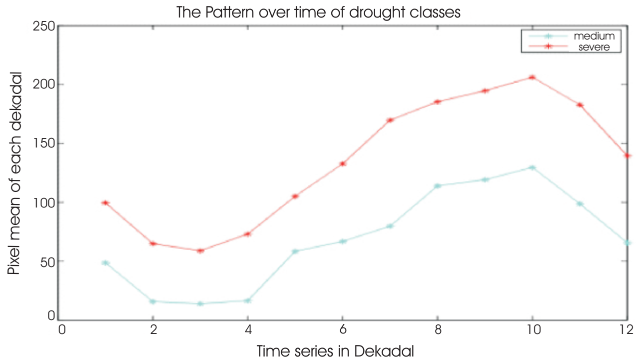

Figure 6. Sample Means of the Intensities of Drought Objects over Time During a Growing Season (1984)

images in the series for a specific location. The mean of intensity value of the objects over the twelve dekadals for a specific region is shown in Figure 5.

The distribution of the mean intensity values in Figure 5 shows that the mean intensity value increases over time and reaches the maximum around the first ten days of September. For further illustration, the pattern of drought for two different locations which experienced moderate and severe drought is shown in Figure 6. The horizontal axis indicates the time in dekadals with in the growing season which includes the months June, July, August and September. For this number of months the authors have twelve ten day (dekadal) points. Figure 6 shows, the horizontal axis numbers which indicate the dekadals in the series, i.e., 1 indicates the first ten days of the June month, 2 indicates the next ten days(from June 11 to 20), and so on.

It is observable from the graph in Figure 6 that the pattern followed by different classes of drought is similar, though the values at each time step in the series differ. This difference in the intensity values helps to note that the extent of severity depend on the pattern followed in the graph. For example, the pattern identified as 'medium' in Figure 6 has lower mean intensity value than the 'severe' one at every time step in the series.

Conclusion

Developments in remote sensing image analysis for drought monitoring for early warning are an ongoing research area. Most of the works so far have been based on the classification of the image region in to drought and non-drought categories at pixel level. And prediction of the probable decrease in crop yield during harvesting is based on this classification results. Though there are certain patterns that drought occurrences could manifest, as shown in this work, there were little considerations. Furthermore, this research also gave an insight to the necessity of time series analysis to take required action early while within the growing season itself.

The system was experimentally analyzed with 108 virtual drought objects making up nine time series for the identified growing season of June to September. Nearly, all of the series over growing season demonstrated similar patterns for historical drought occurrences.

Recommendations

This work introduced the idea of object level analysis of drought from an image. But detail research work is required to group pixels to an object based on the inherent nature of the crop. Thus, the segmentation approach will include the study results of this kind.

Furthermore, this study was based on limited historical image data for drought occurrences. As a result, the time series analysis was based only on the patterns that manifested during those times. But for accurate pattern, the model should incorporate behavior of drought obtained from detail investigation of its historical incidences with different severity levels at different times. In addition, the combination of other parameters like amount of rain fall, duration of sunshine, etc., with the NDVI images is essential for more reliable analysis. Hence, future studies should put this fact in to considerations.

More importantly, the time series of data used in this work was for ten day intervals, which makes the series coarse. Hence, decreasing the series interval will give smooth data and will even help the pattern become more accurate.

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